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MATHEMATICAL APPROACH FOR SELECTION OF WASTE PLASTIC OIL – DIESEL BLENDS

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ABSTRACT

The challenges of waste management and increasing fuel crisis can be addressed simultaneously with the production of fuel from plastic wastes. Global warming and waste management policies have forced for the use of alternative fuels on engines. The production of fuel from plastic wastes will indeed tackle the environmental pollution problem of waste plastic management in the land fills. Plastics being derived from petrochemical source has higher amount of hydrocarbon which yield oil with high calorific value. Engine tests have been carried out using neat Waste Plastic Oil and blends of Waste Plastic Oil in proportions of 25%, 50%, and 75% with diesel as fuel. Combinatorial Mathematics Based Approach (CMBA) has been adapted to choose the optimum blend for superior performance of the engine. Engine performance combustion and emission characteristics under different loads for different test fuels are discussed. The results of CMBA and experimental tests showed that WPO25 is the optimum blend.

KEYWORDS: Waste Plastic Oil; Combinatorial Mathematics Based Approach; Multi Attribute Decision Making; Wpo-Diesel Blend; Permanent Function; Index Score

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Original Article

INTRODUCTION

With ever increasing dependence on fossil fuels, its depletion is zipping and zooming day by day. The shortage of fossil fuels can be overcome with utilization of alternative fuels on diesel engines. Waste plastic oil is one among the various alternative fuels that can be used either as neat fuel or as diesel blend. The raw material cost for production of oil from plastic wastes is zero as they are available at free of cost [1]. Hence, waste plastic oil (WPO) is acclaimed to be a promising alternative fuel. Many researchers have proclaimed that the properties of waste plastic oil are close to diesel [2, 3]. For all biodiesels, the viscosity is higher than that of diesel even though they are esterified [4, 5]. But, WPO has lower viscosity compared to other biodiesels and slightly higher than that of diesel. Hence, no need of esterification, also, little bit of higher viscosity improves the engine lubricity for extending the life of engine.

Multi Attribute Decision Making (MADM) is a discrete approach to identify the optimum alternative, where, predetermined and limited numbers of alternatives are present. Various MADM methods are Simple Additive Weighting (SAW), Weighted Product Method (WPM), Analytical Hierarchy Process (AHP), TOPSIS, Taguchi, Grey Relational Analysis (GRA), Graph Theory Matrix Approach (GTMA) etc. Jadhav [6] investigated the engine performance with Mangifera Indica Methyl Ester and adapted Taguchi grey relational analysis to optimize BSFC and NOx. Six input parameters with five levels were considered to form L25 orthogonal array. Fuel injection nozzle geometry was found to be the most influencing parameter. Razmjooei and Nagarajan [7] adapted Response surface

method to optimize the operating parameters to simultaneously reduce NOx and particulate matter. Dimitriou et al [8] studied the effects of injection rate with EGR combinations and bio-diesel fuel rates. Taguchi orthogonal array with one way analysis of variance have been used to estimate the importance of chosen factors and to find the optimum parameters for reducing the emissions without loss reducing the power. Kadam and Jadhav [9] adapted Taguchi and multiple regression analysis to optimize vibration and performance on a diesel engine. L16 array was formed with Taguchi technique and multi regression analysis was used to find the best relationship between the input and output parameters.

Earlier studies on WPO and its blends as alternative fuel established the virtues of WPO in reducing the exhaust gas emissions. Likewise, a lot of research has been conducted in the past to choose optimum alternative utilizing GRA, RSM, Taguchi approach and so on. A definite study or a tool addressing the selection of optimum blend which is simple, systematic and logical scientific method is needed. The present study envisages analysis of engine performance with various blends of WPO. Combinatorial Mathematical Based Approach is adapted to select the most desired WPO blend that can be suitably tuned to obtain superior performance out of the engine.

2. MATERIALS AND METHODS

2.1. Engine Setup and Procedure

The engine tests were conducted on single cylinder (3.7 kW) constant speed (1500 rpm) four stroke diesel engine. An eddy current dynamometer was coupled to the engine. Various instruments like AVL H12D miniature pressure transducer, AVL 364 angle encoder, AVL Digas 444 gas analyzer, smoke meter of AVL make were used to measure the desired parameters. AVL INDI MICRA-602-T10602A Version V2.5 software was used for online analysis of engine performance. The ignition delay period, starting of combustion, heat release rates and peak cylinder pressure were obtained from Pressure Vs Crank angle diagram. The technical specifications of the engine are shown in Table 1. Tests were conducted at five load conditions i.e. 3A, 6A, 9A, 12A and 15A which correspond to 20%, 40%, 60%, 80% and 100% of load. Engine was run for 10 min at every load to stabilize and the readings were recorded. For each refueling with other blends, engine was run for 30 min to consume the fuel entrapped in the fuel lines. Repeatability was ensured by replicating the experiments thrice. The overall approach is given in Figure 1.

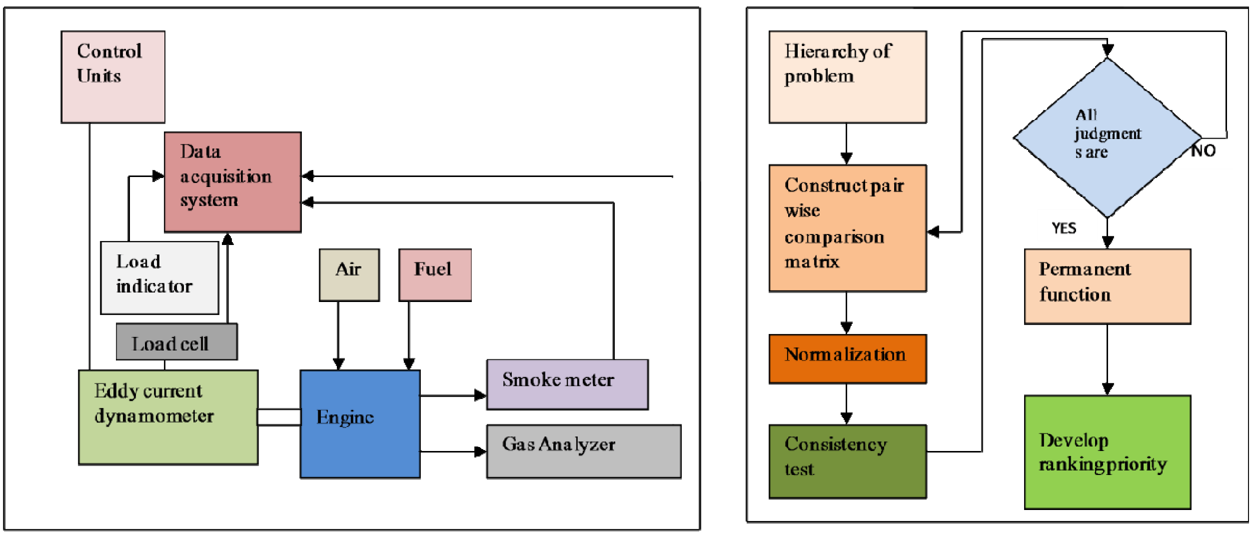

Figure 1: Engine Setup and CMBA Methodology

Table 1: Engine Specifications

Make And Model	Kirloskar, AV1
Number of Cylinders	1
Bore, mm	80
Stroke, mm	110
Compression Ratio	16.5:1
Rated Power, Kw	3.7
Rated Speed, Rpm	1500
Fuel Injection Timing, ^{0}btdc	23
Fuel Injection Pressure, Bar	215
Loading Device	Eddy current dynamometer

3. COMBINATORIAL MATHEMATICAL BASED APPROACH

Combinatorial Mathematical Based Approach (CMBA) is a Multi Attribute Decision Making method, which is an integration of combinatorial mathematics matrix function and Analytical hierarchy process. The objective of CMBA methodology is to identify the factors that influence the engine operating parameters and get the most suitable combination.

The stepwise procedure of CMBA is explained as follows,

Step 1: Decision Matrix

The decision matrix consists of alternatives, attributes and relative importance [10]. In this study, Load and WPO blends are considered as alternatives. BSFC, BTE, NO_x, HC, CO, Smoke and EGT are the attributes. Eq. (1) shows the decision matrix in general form.

$$M = \begin{bmatrix} C_{11} & \cdots & C_{1j}. & \cdots & C_{1B} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ C_{i1} & \cdots & C_{ij} & \cdots & C_{iB} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ C_{A1} & \cdots & C_{Aj} & \cdots & C_{AB} \end{bmatrix} \quad (1)$$

Where, C_{ij} is the performance value and A, B are the number of alternatives and attributes. The attributes are either subjective or objective.

Step 2: Normalization

Normalization makes all values of attributes to be non-dimensional. The normalization procedure adopted in this study is as follows,

$$d_{ij} = \frac{c_{ij}}{\max_j (c_{ij})} \quad \text{; when the } j^{th} \text{ attribute is found to be beneficial} \quad (2)$$

$$d_{ij} = \frac{\min_j (c_{ij})}{c_{ij}} \quad \text{; when the } j^{th} \text{ attribute is found to be non beneficial} \quad (3)$$

Eq. (4) shows the decision matrix with normalized values.

$$M' = \begin{bmatrix} d_{11} & \dots & d_{1j}. & \dots & d_{1B} \\ \dots & \dots & \dots & \dots & \dots \\ d_{i1} & \dots & d_{ij} & \dots & d_{iB} \\ \dots & \dots & \dots & \dots & \dots \\ d_{A1} & \dots & d_{Aj} & \dots & d_{AB} \end{bmatrix} \tag{4}$$

In the present study, BTE is beneficial, whereas BSFC, NO_x, HC, CO, Smoke and EGT are non beneficial. The normalized values of the experimental results are shown in Table 2.

Table 2: Normalized Values of Experimental Results

Exp No.	Fuel	Load (%)	BSFC (kg/h kW)	BTE (%)	NOx (ppm)	HC (ppm)	CO (%)	Smoke (%)	EGT (0C)
1	WPO25	20	0.049	0.024	1.000	0.127	0.922	1.000	1.000
2	WPO25	40	0.345	0.375	0.884	0.392	0.813	0.914	0.759
3	WPO25	60	0.633	0.660	0.652	0.608	0.719	0.741	0.578
4	WPO25	80	0.885	0.869	0.446	0.907	0.422	0.513	0.387
5	WPO25	100	1.000	1.000	0.251	1.000	0.000	0.216	0.156
6	WPO50	20	0.035	0.009	0.989	0.082	0.953	0.984	0.960
7	WPO50	40	0.336	0.322	0.862	0.302	0.859	0.902	0.709
8	WPO50	60	0.619	0.592	0.636	0.526	0.766	0.690	0.492
9	WPO50	80	0.881	0.796	0.417	0.840	0.484	0.404	0.271
10	WPO50	100	0.982	0.932	0.219	0.981	0.047	0.161	0.070
11	WPO75	20	0.022	0.004	0.973	0.019	0.969	0.980	0.899
12	WPO75	40	0.323	0.311	0.826	0.228	0.891	0.894	0.668
13	WPO75	60	0.611	0.548	0.607	0.485	0.828	0.678	0.447
14	WPO75	80	0.872	0.751	0.354	0.799	0.516	0.341	0.226
15	WPO75	100	0.965	0.902	0.148	0.922	0.063	0.090	0.030
16	WPO100	20	0.000	0.000	0.964	0.000	1.000	0.973	0.854
17	WPO100	40	0.310	0.285	0.786	0.194	0.922	0.882	0.613
18	WPO100	60	0.593	0.527	0.571	0.433	0.875	0.667	0.392
19	WPO100	80	0.850	0.705	0.311	0.765	0.578	0.294	0.166
20	WPO100	100	0.947	0.869	0.000	0.854	0.188	0.000	0.000

Step 3: Relative Importance Values for Attributes

The decision maker meticulously analyses the attributes and assign relative importance values (off diagonal elements) using Analytic hierarchy process scale [11, 12]. The pair wise comparison matrix N, as shown in Eq. (5), is formed with p_{ij} and p_{ji} where p_{ij} = 1 when i=j and $p_{ji} = \frac{1}{p_{ij}}$

$$N = \begin{bmatrix} 1 & p_{12} & p_{13}. & \dots & p_{1B} \\ p_{21} & 1 & p_{23} & \dots & p_{2B} \\ p_{31} & \dots & 1 & \dots & p_{3B} \\ \dots & \dots & \dots & \dots & \dots \\ p_{A1} & \dots & p_{A2} & \dots & 1 \end{bmatrix} \tag{5}$$

The scale for pair wise comparison is shown in Table 3 [10].

Table 3: Pair Wise Comparison Scale

Degree of Importance	Definition
1	Equal
2	Intermediate between 1 and 3
3	Moderately preferable
4	Intermediate between 3 and 5
5	Strongly preferable
6	Intermediate between 5 and 7
7	Very strongly preferable
8	Intermediate between 7 and 9
9	Extremely strongly preferable

Pair wise comparison matrix in the present study is shown in Eq. (6),

$$Q = \begin{bmatrix} & BSFC & BTE & NO_x & HC & CO & Smoke & EGT \\ BSFC & 1 & 3 & 2 & 3 & 4 & 6 & 6 \\ BTE & 0.333 & 1 & 2 & 2 & 3 & 3 & 5 \\ NO_x & 0.500 & 0.500 & 1 & 2 & 3 & 3 & 4 \\ HC & 0.333 & 0.500 & 0.500 & 1 & 2 & 4 & 3 \\ CO & 0.250 & 0.333 & 0.333 & 0.500 & 1 & 2 & 2 \\ Smoke & 0.167 & 0.333 & 0.333 & 0.250 & 0.500 & 1 & 3 \\ EGT & 0.200 & 0.250 & 0.333 & 0.500 & 0.333 & 0.333 & 1 \end{bmatrix} \quad (6)$$

The consistency check [13] should be carried out to ensure the judgments of relative importance values of attributes. As per the decision making method, consistency ratio should be less than 0.1. For pair wise comparison matrix shown in Eq. (6), the consistency ratio was found to be 0.061.

Step 4: Matrix for Attributes of Alternatives

Matrix for attributes of every alternative is formed with normalized values as diagonal elements and off diagonal elements is taken from Eq. (6). This matrix is represented as R in Eq. (7).

$$R = \begin{bmatrix} d_{11} & p_{12} & p_{13}. & \cdots & p_{1B} \\ p_{21} & d_{22} & p_{23} & \cdots & p_{2B} \\ p_{31} & \cdots & d_{33} & \cdots & p_{3B} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ p_{A1} & \cdots & p_{A3} & \cdots & d_{AB} \end{bmatrix} \quad (7)$$

In the present study, the alternative selection attribute matrix is shown as Eq. (8).

$$
R = \begin{bmatrix}
d_{11} & 0.507 & 0.308 & 0.324 & 0.289 & 0.310 & 0.250 \\
0.120 & d_{22} & 0.308 & 0.216 & 0.217 & 0.155 & 0.210 \\
0.180 & 0.085 & d_{33} & 0.216 & 0.217 & 0.155 & 0.178 \\
0.120 & 0.085 & 0.077 & d_{44} & 0.145 & 0.207 & 0.125 \\
0.090 & 0.056 & 0.051 & 0.054 & d_{55} & 0.103 & 0.083 \\
0.060 & 0.056 & 0.051 & 0.027 & 0.036 & d_{66} & 0.125 \\
0.072 & 0.042 & 0.051 & 0.054 & 0.024 & 0.017 & d_{66}
\end{bmatrix} \tag{8}
$$

Step 5: Permanent Function

The “index score”, is also called as Permanent function (Per C) [12] and is calculated as follows,

$$
\begin{aligned}
&Per\ (C) = \\
&\prod_{i=1}^{A} P_i + \sum_{i=1}^{A-1} \sum_{j=i+1}^{A} \dots\dots\dots\ ..\sum_{A=t+1}^{A} (p_{ij}\, p_{ji}) P_k P_l P_m P_n P_o \dots. P_t P_m \\
&+ \sum_{i=1}^{A-2} \sum_{j=i+1}^{A-1} \sum_{k=j+1}^{A} \dots\dots. \sum_{A=t+1}^{A} (p_{ij}\, p_{jk}\, p_{ki} + p_{ik}\, p_{kj}\, p_{ji}) P_l P_m P_n P_o \dots. P_t P_M \\
&+ [\sum_{i=1}^{A-3} \sum_{j=i+1}^{A} \sum_{k=i+1}^{A-1} \sum_{l=i+2}^{A} \dots\dots\dots\ \dots \sum_{A=t+1}^{A} (p_{ij}\, p_{ji})(p_{kl}\, p_{lk}) P_m P_n P_o \dots.. P_t P_M + \\
&\sum_{i=1}^{A-3} \sum_{j=i+1}^{A-1} \sum_{k=i+1}^{A} \sum_{l=j+1}^{A} \dots. \sum_{A=t+1}^{A} (p_{ij}\, p_{jk}\, p_{kl}\, p_{li} + p_{il}\, p_{lk}\, p_{kj}\, p_{ji}) P_m P_n P_o \dots.. P_t P_m] \\
&+ [\sum_{i=1}^{A-2} \sum_{j=i+1}^{A-1} \sum_{k=j+1}^{A} \sum_{l=1}^{A-1} \sum_{m=l+1}^{A} \dots\dots. \sum_{A=t+1}^{A} (p_{ij}\, p_{jk}\, p_{ki} + p_{ik}\, p_{kj}\, p_{ji})(p_{lm}\, p_{ml}) P_n P_o \dots\dots P_t P_m \\
&+ \sum_{i=1}^{A-4} \sum_{j=i+1}^{A-1} \sum_{k=i+1}^{A} \sum_{l=i+1}^{A} \sum_{m=j+1}^{A} \dots\dots\dots \sum_{A=t+1}^{A} (p_{ij}\, p_{jk}\, p_{kl}\, p_{lm}\, p_{mi} + p_{im}\, p_{ml}\, p_{lk}\, p_{kj}\, p_{ji}) P_n P_o \dots\dots P_t P_m] \\
&+ [\sum_{i=1}^{A-3} \sum_{j=i+1}^{A-1} \sum_{k=i+1}^{A} \sum_{l=j+1}^{A} \sum_{m=1}^{A-1} \sum_{n=m+1}^{A} \dots\dots.. \sum_{A=t+1}^{A} (p_{ij}\, p_{jk}\, p_{kl}\, p_{li} + p_{il}\, p_{lk}\, p_{kj}\, p_{ji})(p_{mn}\, p_{nm}) P_o \dots\dots P_t P_m \\
&+ \sum_{i=1}^{A-5} \sum_{j=i+1}^{A-1} \sum_{k=j+1}^{A} \sum_{l=1}^{A-2} \sum_{m=l+1}^{A-1} \sum_{n=m+1}^{A} \dots\dots. \sum_{A=t+1}^{A} (p_{ij}\, p_{jk}\, p_{ki} + p_{ik}\, p_{kj}\, p_{ji})(p_{lm}\, p_{mn}\, p_{nl} + p_{\ln}\, p_{nm}\, p_{ml}) P_o \dots\dots. P_t P_m \\
&+ \sum_{i=1}^{A-5} \sum_{j=i+1}^{A} \sum_{k=i+1}^{A-3} \sum_{l=i+2}^{A} \sum_{m=k+1}^{A-1} \sum_{n=k+2}^{A} \dots\dots. \sum_{A=t+1}^{A} (p_{ij}\, p_{ji})(p_{kl}\, p_{lk})(p_{mn}\, p_{nm}) P_o \dots\dots. P_t P_m \\
&+ \sum_{i=1}^{A-5} \sum_{j=i+1}^{A-1} \sum_{k=i+1}^{A} \sum_{l=i+1}^{A} \sum_{m=i+1}^{A} \sum_{n=j+1}^{A} \dots.. \sum_{A=t+1}^{A} (p_{ij}\, p_{jk}\, p_{kl}\, p_{lm}\, p_{mn}\, p_{ni} + p_{in}\, p_{nm}\, p_{ml}\, p_{lk}\, p_{kj}\, p_{ji}) P_o \dots.. P_t P_m] \\
&+ \dots\dots\dots\ \dots\dots\dots
\end{aligned}
$$

A computer program was generated to simplify the above calculation.

Step 6: Rank of Alternatives

Calculate the index scores for all alternatives using step 5 and sort either in descending order. The alternative with highest index score is ranked as lowest from among the alternatives.

4. RESULT OF CMBA

As an example, index score for alternative 1 is presented below,

The alternative selection attribute matrix is given as (Step 4),

$$R = \begin{bmatrix} 0.049 & 0.507 & 0.308 & 0.324 & 0.289 & 0.310 & 0.250 \\ 0.120 & 0.024 & 0.308 & 0.216 & 0.217 & 0.155 & 0.210 \\ 0.180 & 0.085 & 1.000 & 0.216 & 0.217 & 0.155 & 0.178 \\ 0.120 & 0.085 & 0.077 & 0.127 & 0.145 & 0.207 & 0.125 \\ 0.090 & 0.056 & 0.051 & 0.054 & 0.922 & 0.103 & 0.083 \\ 0.060 & 0.056 & 0.051 & 0.027 & 0.036 & 1.000 & 0.125 \\ 0.072 & 0.042 & 0.051 & 0.054 & 0.024 & 0.017 & 1.000 \end{bmatrix} \quad (10)$$

The index score calculated for experiment no. 1 as shown in Eq. (10) is 1.2585. Likewise, the index scores for all experiments are calculated and tabulated to rank them and are shown in Table 4.

Table 4: Rank of the Alternatives

Rank	Experiment No.	Fuel	Load (%)	Index Score
1	5	WPO25	100	1.2585
2	9	WPO50	80	1.2364
3	14	WPO75	80	1.2101
4	3	WPO25	60	1.2029
5	19	WPO100	80	1.1938
6	4	WPO25	80	1.1821
7	8	WPO50	60	1.1749
8	10	WPO50	100	1.1660
9	13	WPO75	60	1.1624
10	18	WPO100	60	1.1464
11	15	WPO75	100	1.1352
12	20	WPO100	100	1.1127
13	2	WPO25	40	1.0897
14	7	WPO50	40	1.0650
15	12	WPO75	40	1.0463
16	17	WPO100	40	1.0313
17	1	WPO25	20	0.9407
18	6	WPO50	20	0.9313
19	11	WPO75	20	0.9178
20	16	WPO100	20	0.9131

Table 4 shows that, index score for experiment no. 4 is highest among all experiments. As such, WPO25 at 100% load is found to be the optimum blend for superior performance of the engine. CMBA methodology was adapted by [14-20] in manufacturing process and similar type of findings were reported.

CONCLUSIONS

The present study is to analyze diesel engine performance combustion and emission characteristics using blends of WPO and to find the optimum blend for superior performance of the engine. The following conclusions are drawn out of this study:

1. The properties of all WPO blends are acceptable and favorable as fuel on diesel engine.
2. Engine operated smoothly not only with WPO blends but also with 100% WPO.
3. Waste plastic oil blend of WPO25 at 100% load is found to be the best blend for superior performance of the engine based on performance and emission characteristics. The proposed method of CMBA considers any number

of quantitative and qualitative attributes. Also, it offers objective and simple assessment approach. The concept of permanent function provides complete information without any loss.

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